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# INTELLIGENT DRILLING RATE PREDICTOR

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Abstract. *Drilling rate prediction is crucial for improving the performance of drilling. However, large number of unforeseen factors and events influence the drilling rate and make it a complex and stochastic process. Consequently, prediction of drilling rate has remained challenging during last decades. Many different techniques have been introduced for this mission. Among those, Bourgoyne and Young model (BYM) has been widely used during last decades. BYM has been made up of eight functions. Each function represents the effect of some drilling parameters. Although the relationship between drilling rate and mentioned eight functions is nonlinear and very complex, Bourgoyne and Young simply multiplied all eight functions with each other to attain the drilling rate. In this research, after determining constant coefficients of Bourgoyne and Young model using Genetic Algorithm, a General Regression Neural Networks (GRNN) is employed hierarchically in order to uncover the complex relation saof drilling rate and mentioned eight functions of BYM. The data sets used in this study are nine wells of an Iranian gas field called "Khangiran". Simulation results show that the proposed approach is more accurate than a GABYM in drilling rate prediction.*

**Keywords:** Neural networks (NN), Bourgoyne and Young model (BYM), General regression neural networks (GRNN), Drilling rate prediction, Genetic algorithm (GA)

1. **Introduction.** Drilling engineers have been concerned about drilling rate prediction extensively during last decades because it is essential for optimum drilling parameters selection, which is important to decrease drilling cost per foot [1,2].

Rate of penetration is affected by many parameters. Such as, hydraulics, weight on bit, rotary speed, bit type, mud properties and formation characteristics [3]. Unfortunately, there exists no explicit mathematical relationship between drilling rate and different drilling factors. This is due to the large number of drilling parameters influencing the drilling rate. Furthermore, the relationship of these factors to each other and to drilling rate is nonlinear and complex [4]. However, experts have put forward some suggestions to address this issue. They have succeeded to model the effects of different drilling parameters involving drilling rate as mathematical functions. One of those methods is Bourgoyne and Young model (BYM), which is widely used in practice [5]. The Architecture of this method is demonstrated in Figure 1.

As can be interpreted from Figure 1, Bourgoyne and Young have introduced simplified models, which map important drilling variables onto its rate.

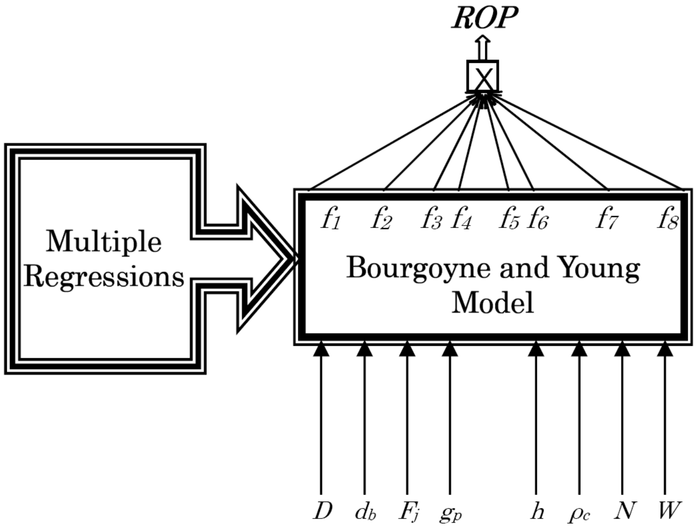


FIGURE 1. Architecture of BYM

In Figure 1, $ROP$ is rate of penetration (ft/hr), $D$ is True vertical depth (ft), $d_b$ is Bit diameter (in), $F_j$ is Jet impact force (lbf), $g_p$ is Pore Pressure gradient (lbm/gal), $h$ is Fractional bit tooth wear, $\rho_c$ is Equivalent mud density (lbm/gal), $N$ is Rotary speed (rpm) and $W$ is Weight on Bit (1000 lbf). The function $f_1$ represents the effect of formation strength, bit type, mud type and solid content, which are not included in the drilling model. This term is expressed in the same unit as penetration rate and is often called the formation drillability. Furthermore, the functions $f_2$ and $f_3$ symbolize the effect of compaction on penetration rate. The function $f_4$ signifies the effect of overbalance on penetration rate. The functions $f_5$ and $f_6$ model the effect of bit weight and rotary speed on penetration rate respectively. The function $f_7$ represents the effects of tooth wear and the function $f_8$ characterizes the effect of bit hydraulics on penetration rate [2]. As can be seen in this figure, all eight functions are multiplied to each other to reach the $ROP$. However, the relationship of mentioned functions and the drilling rate can be much more complex in practice. The main contribution of this paper is to disclose the real relation of $ROP$ and eight functions of BYM using GRNN.

It is important to note that there are some unknown parameters or coefficients in this model, which must be determined based on prior drilling experiences in the field. It is taken for granted that the method of determining these coefficients has a significant impact on the accuracy of the model. BYM designers suggested multiple regression method to determine unknown coefficients [5]. However, applying multiple regression method does not guarantee reaching physically meaningful coefficients and functions. To reach meaningful results, Non-linear least square data fitting with trust-region method have recently been applied to this problem [6]. This method is one of the optimization algorithms, which minimizes the sum of square errors function. The method is based on the interior-reflective Newton method. In each of iterations, the approximate solution of a large linear system is estimated using the method of *preconditioned conjugate gradients* (PCG) [7,8]. This technique makes it possible to determine lower and upper bounds for results and limits them to be in the reasonable ranges [8]. However, this technique does not yield reasonable accuracy. Moradi and his colleagues have recently introduced a new drilling model utilizing soft computing [9]. Although this method improved the accuracy marginally, it provides no information about drillability of different formations of the field. In other words, this approach works like a black box, which receives inputs and calculates the drilling rate as output. But, no further information about the drilling can be interpreted from the model.

To continue the last efforts, in this paper, we introduce an innovative technique, which uses GA to provide physically meaningful coefficients for BYM. In this method, GRNN is utilized to uncover nonlinear and complex relationship between drilling rate and aforementioned eight functions of BYM. This method not only increases the prediction accuracy considerably, but it also provides required drilling information of the field such as drillability.

In fact, ANNs have been successfully applied to different applications in the field of petroleum industry such as reservoir characterization [10], optimum bit selection [11], trap quality evaluation [12] during past decades. ANN has many features that make it attractive to use in such problems. Among those, however, the ability to deal with ill-defined and noisy real signals and datasets and to provide a robust and accurate pattern recognition and model identifier scheme are the most important ones [13-15]. Therefore, ANN can provide an appropriate method for uncovering the complex relationship between drilling rate and above-mentioned eight functions.

The rest of the paper is organized in the following manner. First, we commence with the debut of Bourgoyne and Young drilling rate model. Then, Khangiran Iranian gas field is introduced. Next, intelligent drilling rate predictor is elaborated. And we conclude with presenting the simulation results on Khangiran Iranian gas field, and comparing them with GA aided BYM method.

2. **Bourgoyne and Young Drilling Rate Model.** Bourgoyne and Young have proposed the following equation to model the drilling process when using roller cone bits (1):

$$Rop = f_1 \times f_2 \times f_3 \times f_4 \times f_5 \times f_6 \times f_7 \times f_8 \tag{1}$$

The functional relations in Equation (1) are as follows.

$$f_1 = e^{2.303 a_1} = K \tag{2}$$

$$f_2 = e^{2.303 a_2 (10000 - D)} \tag{3}$$

$$f_3 = e^{2.303 a_3 D^{0.69} (g_p - 9)} \tag{4}$$

$$f_4 = e^{2.303 a_4 D (g_p - \rho_c)} \tag{5}$$

$$f_5 = \left[ \frac{\frac{W}{d_b} - \left(\frac{W}{d_b}\right)_t}{4 - \left(\frac{W}{d_b}\right)_t} \right]^{a_5} \tag{6}$$

$$f_6 = \left(\frac{N}{60}\right)^{a_6} \tag{7}$$

$$f_7 = e^{-a_7 h} \tag{8}$$

$$f_8 = \left(\frac{F_j}{1000}\right)^{a_8} \tag{9}$$

where, $a_1$ to $a_8$ are BYM constant coefficients and $(W/d_b)_t$ is Threshold bit weight per inch of bit diameter at which the bit begins to drill.

The value of parameters $a_1$ to $a_8$ depend on local drilling conditions and must be determined for each formation separately using prior drilling data sets obtained from the drilling area [2]. Bourgoyne and Young Recommended specific bounds for each of eight coefficients, and these boundaries are based on reported ranges for the coefficients from various formations in different area [2,5], and they averaged the values of them. Lower and upper bounds to achieve meaningful results have been suggested as shown in the Table 1. Using these bounds increases the reliability of the achieved predictor system.

TABLE 1. Borgoyne and Young recommended bounds for each coefficient

| Coefficients | Lower bound | Upper bound |
|---|---|---|
| $a_1$ | 0.5 | 1.9 |
| $a_2$ | 0.000001 | 0.0005 |
| $a_3$ | 0.000001 | 0.0009 |
| $a_4$ | 0.000001 | 0.0001 |
| $a_5$ | 0.5 | 2 |
| $a_6$ | 0.4 | 1 |
| $a_7$ | 0.3 | 1.5 |
| $a_8$ | 0.3 | 0.6 |

Bourgoyne and Young employed multiple regression method to determine unknown coefficients. But, this scheme provides results out of recommended bounds in some situations. To be more precise, multiple regression method may result in negative or zero values. It is taken for granted that negative or zero values for coefficients are physically meaningless. For instance, if the weight on bit constant ($a_5$) is a negative value, it illustrates that increasing the weight on bit leads to reduce the penetration rate or a zero value implies that increasing the weight on bit has no effect on the drilling rate. Therefore, it is needed to apply new methods to gain an applicable predictor system.

3. **Khangiran Gas Field.** Khangiran gas field is located in the northeast of Iran. This field was surveyed in 1937. In 1956, the stratigraphy plan was prepared and it was named in 1962. Figure 2 illustrates the formations of Khangiran gas field [16].

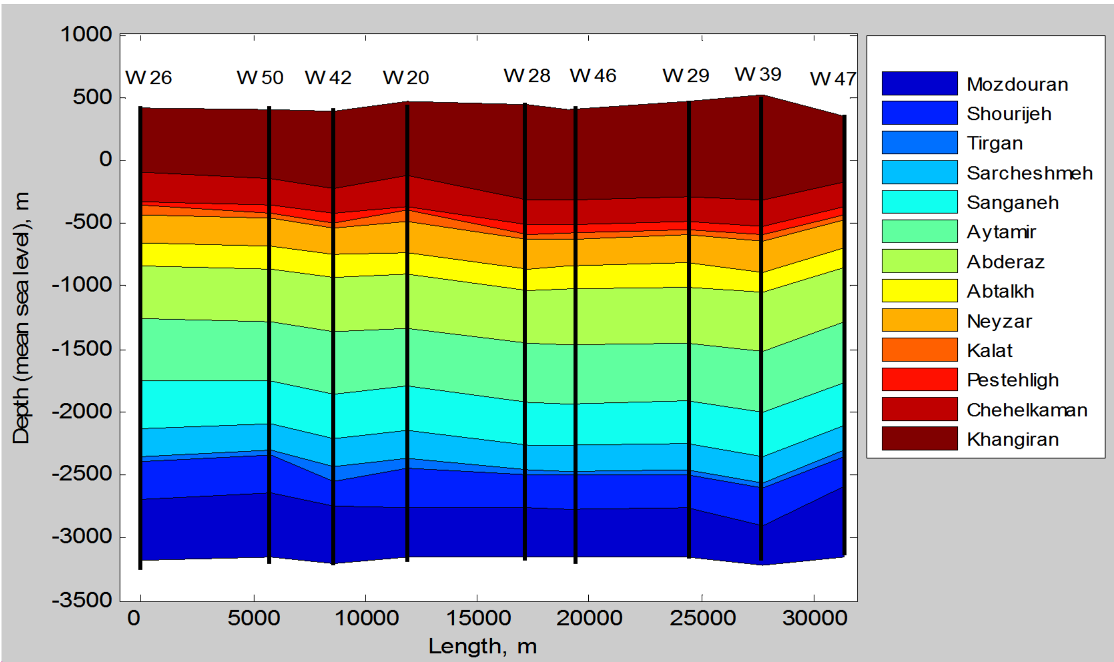


FIGURE 2. The formations of Khangiran gas field

Khangiran gas field is located in the northeast of Iran. This field was surveyed in 1937. In 1956, the stratigraphy plan was prepared and it was named in 1962. Figure 2 illustrates the formations of Khangiran gas field [16].

Khangiran field includes three gas reservoirs:

- Mozdouran: The existence of sour gas in this reservoir was proved in 1968 and the production was started in 1983. It consists of thick layer limestone. Up to now, 37 wells have been drilled.
- Shourijeh B: This reservoir was explored in 1968 and production was started in 1974. Shourigeh formation is mainly formed from sandstone layers. So far, seven wells have been drilled and completed in the reservoir. The gas from this reservoir is sweet and H2S free.
- Shourijeh D: This reservoir was explored in 1987 and after drilling the well, production was started in the same year. Seven wells have been drilled up to now. The gas from this reservoir is sweet, too.

4. **Implementing Intelligent Drilling Rate Predictor in Khangiran Iranian Gas Field.** The intelligent drilling rate predictor is implemented in Khangiran field. To apply proposed method, the following procedure was performed.

(1). The daily drilling progress reporting different drilling parameters of 10 drilled wells (from the surface to the final reservoir depth) in this field were gathered initially. After controlling data quality, nine wells which representing more accurate data were extracted.

(2). A database was constructed from available data of nine wells. The database includes quantities of $D$, $W$, $d_b$, $N$, $g_p$, $\rho_c$, $h$, $F_j$ and achieved $ROP$ in each formation. It must be noted that the fractional tooth wear ($h$) is expressed just at the end of bit running. Therefore, only drilling data at ending the bit run can be used. Table 2 shows a part of required data for partitioning the proposed intelligent method in a formation of Khangiran field called Sarcheshmeh. This date set is included in our database.

(3). For determining constant coefficient of BYM and training the mentioned GRNN method, a training data set is formed by randomly choosing 75% of available data for each formation. The remaining data is used for testing the proposed method.

(4). In each formation, by applying inputs ($D$, $W$, $N$, $g_p$, $\rho_c$, $h$ and $F_j$) and output ($ROP$) to the above-mentioned model we use GA to find out optimum values of eight unknown coefficients. GA is run in the following steps.

    i. Set the initial parameters for GA: population size, crossover type and probability, and mutation probability.
    ii. Set all bounds recommended by Bourgoyne and Young for each of eight parameters particularly.
    iii. Generate the initial population randomly.
    iv. Reckon a fitness value for each subject. The considered fitness function is Standard Deviation of distances between real $ROP$ and estimated $ROP$ by predictor system.
    v. Select the subjects that will mate according to their share in the population global fitness.
    vi. Apply the genetic operators (crossover, mutation ...).
    vii. Repeat Steps 3 to 6 until the generation number is reached.

Figure 3 assists to enlighten this stage of the proposed method. As it is illustrated in Figure 3, Bourgoyne and Young simply multiplied all functions to estimate $ROP$ while the relation of these functions can be nonlinear and very complex.

(5). We utilized a GRNN in a hierarchical manner in order to expose the relationship of afore-mentioned functions. Obviously, uncovering relationship of functions leads to a significant rise in drilling rate prediction accuracy. Figure 4 demonstrates the

TABLE 2. A sample of required data, obtained from wells daily drilling progress reports

| | Well No. | R (ft/hr) | $D$ (ft) | $W$ (1000lbf) | $d_b$ (in.) | $N$ (Rpm) | $\rho_c$ (lbm/gal) | $h$ (%) | $g_p$ (lbm/gal) | $F_j$ (lbf) |
|---|---|---|---|---|---|---|---|---|---|---|
| SARCHESHMEH | well 46 | 3.44 | 9058 | 12.25 | 27.5 | 110 | 11.9 | 1 | 10.6 | 859 |
| | well 42 | 2.57 | 9203 | 12.25 | 22.5 | 110 | 11.9 | 1 | 10.6 | 934 |
| | well 42 | 1.82 | 9098 | 12.25 | 35 | 120 | 11.9 | 1 | 10.6 | 991 |
| | well 42 | 3.28 | 9304 | 12.25 | 22.5 | 110 | 11.9 | 1 | 10.6 | 934 |
| | well 29 | 2.46 | 9396 | 12.25 | 35 | 100 | 11.6 | 1 | 10.3 | 864 |
| | well 29 | 2.18 | 9570 | 12.25 | 35 | 100 | 11.6 | 1 | 10.3 | 1067 |
| | well 28 | 2.73 | 9009 | 12.25 | 30 | 110 | 11.96 | 1 | 10.6 | 1427 |
| | well 28 | 3.82 | 9176 | 12.25 | 30 | 110 | 11.96 | 1 | 10.6 | 1427 |
| | well 28 | 3.28 | 9288 | 12.25 | 30 | 110 | 11.96 | 1 | 10.6 | 1427 |
| | well 26 | 1.31 | 8980 | 12.25 | 40 | 60 | 11.3 | 0 | 9.89 | 875 |
| | well 26 | 1.59 | 9058 | 12.25 | 30 | 80 | 11.3 | 0 | 9.89 | 762 |
| | well 20 | 4.29 | 9137 | 12.25 | 30 | 120 | 11.49 | 1 | 10.2 | 992 |
| | well 20 | 3.28 | 9334 | 12.25 | 30 | 120 | 11.69 | 1 | 10.4 | 1010 |
| | well 20 | 1.45 | 9557 | 12.25 | 30 | 120 | 12.1 | 0 | 10.8 | 840 |

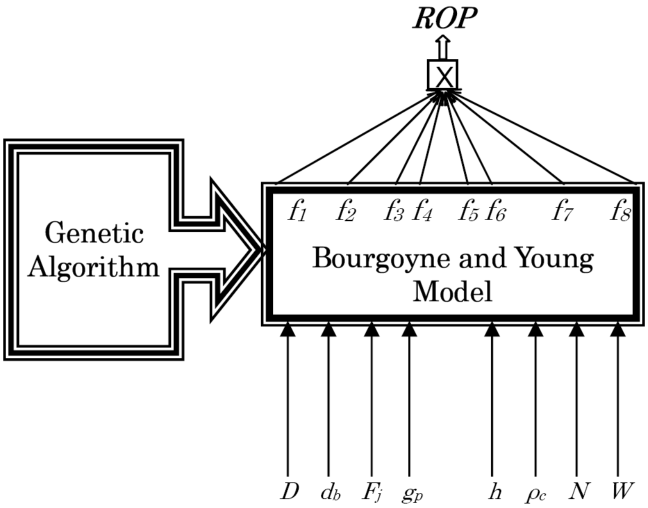


FIGURE 3. Appling GA to BYM for determining its coefficients

architecture of the proposed method after coefficients determination stage in details. As can be interpreted from Figure 4, by applying inputs ($D$, $W$, $N$, $d_b$, $g_p$, $\rho_c$, $h$ and $F_j$) to BYM, eight functions are calculated. Calculated functions as inputs of GRNN and $ROP$ as output of GRNN provide patterns of training the GRNN.

5. **Simulation Results.** In order to test the proposed intelligent predictor the following procedure is performed.

(1). A testing data set is formed using 25% of all available data for each formation. Note that the testing data set was not used in training phase.
(2). By applying values of $D$, $W$, $N$, $d_b$, $g_p$, $\rho_c$, $h$ and $F_j$ in each formation to BYM, values of eight functions are computed.
(3). By feeding eight functions of BYM as inputs to the GRNN, the values of $ROP$ are computed.

(4). Mean Squared Error (MSE) of $ROP$ estimation is calculated for each formation.

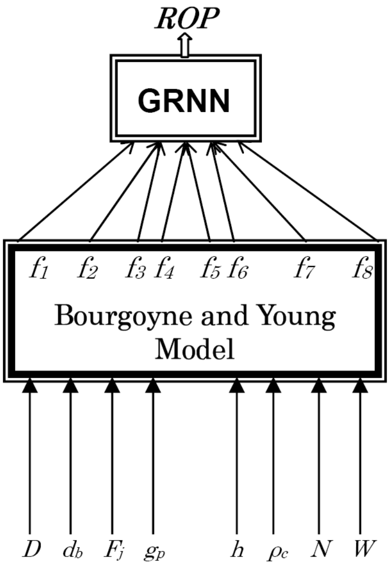


FIGURE 4. Architecture of the proposed hierarchical drilling rate predictor method

We repeated training and testing phase of the proposed method for 1000 times. Mean of values which are computed in the fourth step in testing phase over 1000 times for some formations of Khangiran field are illustraited in Figure 5. For comparison purpose, results obtained from using two conventional methods, namely Fuzzy-SA [15] and BYM with Trust-Region [16], are represented too. Improvement obtained by the proposed method to two conventional methods can be seen in Table 3. It can be interpreted that the proposed scheme is more effective than conventional ones as it presents more accuracy.

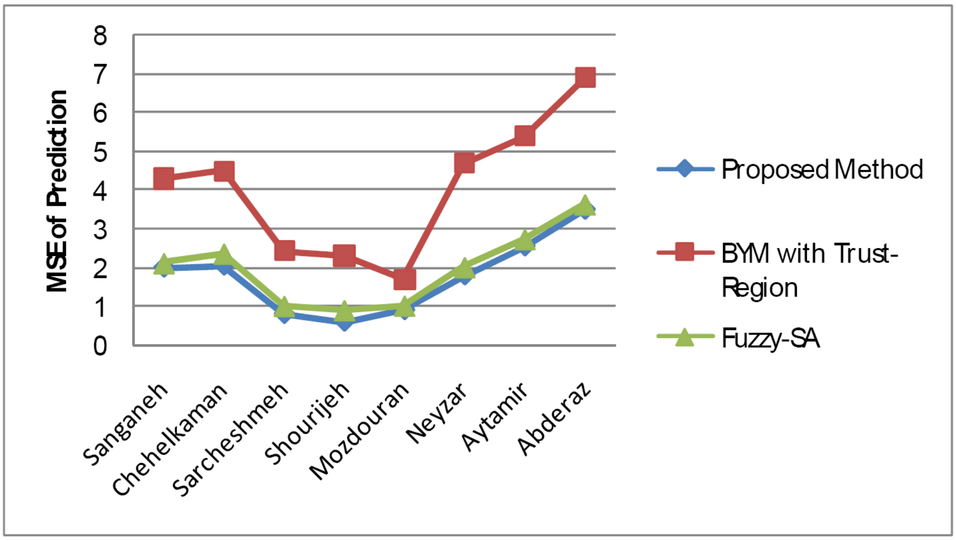


FIGURE 5. Prediction accuracy of proposed method, Fuzzy-SA approach and BYM with Trust-Region

In fact, the first term of Bourgoyne and Young penetration rate model is called the drillability of a formation. Drillability of the formations is very important. It is a measure which shows that how easily the formation can be drilled [2]. This factor is related to the formation physical and mechanical parameters like rock strength, porosity, permeability,

Table 3. Improvement obtained by the proposed method to two conventional methods

| Formation | Improvement to Fuzzy-SA (%) | Improvement to BYM with Trust-Region (%) |
|---|---|---|
| Sanganeh | 4.76 | 53.48 |
| Chehelkaman | 12.76 | 54.44 |
| Sarcheshmeh | 19.19 | 67.07 |
| Shourijeh | 31.81 | 73.91 |
| Mozdouran | 10.00 | 47.05 |
| Neyzar | 10.00 | 61.70 |
| Aytamir | 6.59 | 52.77 |
| Abderaz | 3.58 | 49.27 |
| *TOTAL* | *98.69* | *459.69* |

compaction etc. If the constant $a_1$ is known for each formation, the relevant drillability of that formation can be specified. Computed drillability quantities using proposed method and BYM with Trust-Region are illustrated in the Table 4. It is important to note that Fuzzy-SA approach is unable to provide drillability information. As can be interpreted from this table computed drillabilities for two formations, namely Mozdouran and Neyzar, are very huge when BYM with Trust-Region method is used. We know that it is impossible to have such a huge amount for drillability. Therefore, it can be concluded that using BYM with Trust-Region may leads to invalid answers, while this problem do not exist for the proposed method.

Table 4. Computed drillabilities for Khangiran field formations using proposed method and BYM with Trust-Region

| | Computed Drillability (ft/hr) | |
|---|---|---|
| **Formation** | Proposed method | BYM with Trust-Region |
| **Sanganeh** | 7.292 | 8.85 |
| **Chehelkaman** | 8.3 | 10.31 |
| **Sarcheshmeh** | 13.13 | 18.99 |
| **Shourijeh** | 7.60 | 8.26 |
| **Mozdouran** | 4.8395 | 4.1469e+009 |
| **Neyzar** | 5.815 | 4.9567e+011 |
| **Aytamir** | 6.65 | 8.75 |
| **Abderaz** | 8.11 | 9.06 |

6. **Conclusions.** One of the most important issues in drilling cost optimization is accurate drilling rate prediction. A simplified model of drilling is called Bourgoyne and Young, which define a general mapping between drilling rate and some drilling parameters. The model is widely used in practice. Bourgoyne and Young succeed to model the effect of different drilling parameters in eight mathematical functions. However, their relation to each other and to drilling rate has remained unknown. The major contribution of this paper is to determine the unknown relationship of functions to drilling rate utilizing GRNN. In this research, first, we determined coefficients of BYM using GA and then employed GRNN hierarchically to unearth the relationship of BYM functions. Applying proposed method to an Iranian gas field visualizes the effectiveness of this method in drilling rate prediction.

Although the proposed scheme provides excellent results in simulation, it may not work as well in practice. Because only eight parameters of drilling ($D$, $W$, $N$, $d_b$, $g_p$, $\rho_c$, $h$ and $F_j$) were considered in the proposed method while many other parameters such as the type of bit influence the drilling operation significantly. To increase the accuracy of drilling rate prediction the effect other important parameters should be modeled in future works.

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